Behavioral drowsiness detection system execution based on digital camera and MTCNN deep learning

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ABSTRACT

Drowsy driving is a major cause of road accidents worldwide, necessitating the development of effective drowsiness detection systems. Each year, there are more accidents and fatalities than ever before for a variety of causes. For instance, there were 22,952 fatalities and 79,545 injuries as a result of nearly 66,500 vehicle accidents in the last 10 years. In this paper, we propose a novel approach for detecting drowsiness based on behavioral cues captured by a digital camera and utilizing the multi-task cascaded convolutional neural network (MTCNN) deep learning algorithm. A high-resolution camera records visual indications like closed or open eye movement to base the technique on the driver's behavior. In order to measure a car user's weariness in the present frame of reference, eyes landmarks are evaluated, which results in the identification of a fresh constraint known as "eyes aspect ratio." A picture with a frame rate of 60 frames per second (FPS) and a resolution of 4,320 eyeballs was used. The accuracy of sleepiness detection was more than 99.9% in excellent lighting and higher than 99.8% in poor lighting, according to testing data. The current study did better in terms of sleepiness detection accuracy than a lot of earlier investigations.

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1. INTRODUCTION

Today, a wider range of jobs require the ability to pay attention. Those who employ in the transportation sector like car and truck drivers, steersmen, and airline pilots must maintain a constant watch on the road in order to react swiftly to any unforeseen situations (such as vehicle accidents, dogs getting, and loose while driving) [1]. Driver fatigue brought on by spending extended periods of time behind the wheel reduces the chance of a review. According to research results presented at the International Workshop on relax disorders, drowsy driving contributes to 30% of traffic accidents [2].

An experiment using a driving simulation revealed results that were published in the English magazine “what car?” they concluded that a defective driver poses a considerably greater risk than someone whose blood alcohol content is 25% higher than the allowable limit. Driver weariness can result in micronaps (such as a loss of concentration or a catnap lasting between one and thirty seconds) as well as sleeping behind the wheel [3].

Each year's National Relaxation Structure in 2012 oversleep according to the American poll, 20% of employees have driven when fatigued at least once per month in the preceding year. About 40% of learning operators said that they invite fact-guided sleepy at least as quickly as they did earlier in the month. More than 25% of individuals who had been helped to get fatigued had slept off and rested. Studies have shown that fatigue may impair driving ability on a par with or even more than drinking; these facts and their consequences serve as descriptions of the problem [4]. Due to sluggish driving demands that analytical study in this area continues, ways of life have to be conserved.

Previous research on the detection of alcohol abuse shows that the use of devices and learning techniques may help prevent and also minimize these collisions and their consequences. These methods, together with the application of driving performance indicators based on the distinctive idea of street environment and directing, may accurately identify the distinction between a trashed driver and a free driver [4]. The suggested system uses the openCV and Dlib libraries in the Python integrated development environment (IDE) to continually take images and measure the condition of the eye, mouth, and head in accordance with the defined methodology.

2. LITERATURE REVIEW

According to the source of the data used for the drowsiness measuring, there seem to be two different ways to assess a driver's levels of drowsiness. While some systems monitor the state of the vehicle to determine the driver's level of fatigue, other systems use metrics collected directly from the driver. Lane departures or steering wheel behaviors are the metrics that are most frequently studied in studies of the vehicle condition and its link to weariness.

Gromer *et al.* [3] presents the creation of a low-cost electrocardiogram (ECG) sensor for detecting tiredness using heart rate variability (HRV) data. Designing hardware and software is part of the job. On a printed circuit board (PCB), the hardware was created PCB that was meant to be used as a shield for the Arduino. A low-pass filtered double inverted ECG channel is included on the PCB, as well as there are double outputs that are analog for Arduino is a microcontroller board that may be to connect to and control the digital-to-analog converter. The signal of ECG in digital format is sent for processing a NVidia embedded computer, which includes detection of the QRS complexes, heartbeat, HRV, as well as visuals capabilities. A special PCB design catches the ECG in this development. For quick prototyping, the PCB may be plugged into a normal Arduino board. The signal capture was upgraded to make it more dependable and usable in an automobile setting. However, an ECG can still be detected if the electrodes are connected incorrectly. A two-channel approach is currently used for signal capture. The signal processing was done with the aid of a modular piece of software that ran an algorithm. It is utilized to identify a complex of QRS pattern and to put HR and HRV into practice, which are generated from the complex of QRS.

Research by Solaz *et al.* [5], robustness in the face of various sorts of users and conditions has been investigated in the current study and use small system in vehicle cameras with a lot of movement is presented. Images will be analyzed to determine the chest/abdominal movement of the driver to calculate breathing rate. These data will be examined by using real-time a proven a movement-analysis algorithm and determines driver's the level of weariness and drowsiness. In this experiment proved using a single camera on board that image technology may be used to determine a car driver's breathing rate. First experiment revealed that thoracic respiratory movement may be monitored using a depth map created using inexpensive infrared cameras.

Lee *et al.* [6] explained the goal of his study is to look at the sturdy and recognizable HRV signal patterns obtained from ECG or photoplethysmogram (PPG) sensors worn on the body for detecting drowsiness in the driver. The three varieties of recurrence plots (Bin-RP, Cont-RP, and ReLU-RP). By extracting and learning sleepiness, ReLU-RP was able to discriminate between sleepy and awake states when utilized as the input to convolutional neural network (CNN). R-R interval of heartbeats have features with a pattern of vertical (or horizontal) lines. To determine the efficacy of the presented models in detecting realistic sleepiness.

Chellappa *et al.* [7] suggest a system which was built for four-wheelers, and it detects and notifies the driver's tiredness or drowsiness. The suggested solution would employ a 5-megapixel Raspbian camera to record and evaluate photos of the driver's face and eyes in order to detect driver drowsiness. This method fatigue is evaluated by applying a haar cascade classifier to recognize eye and face cues, particularly facial features and computing between the eyes' euclidean distance to calculate the eye aspect ratio (EAR). The ability to assess sleepiness level had been aided by faces in every frame and reliable eye detection. The frequency of head tilting and eye blinking is appropriately assessed and contributes to indicate sleepiness.

Naqvi *et al.* [8] recommended a project including a universal serial bus (USB) camera for an eye-blink monitoring system, as well as a buzzer that informs the driver when they are drowsy. Global positioning system (GPS) may be used to track the driver's whereabouts. The suggested web application design will allow the administrator to adjust the system's parameters and send messages to a colleague. The project's

goal is to assist in the cost-effective solution of real-world problems. The buzzer is sounded if the driver becomes tired and shuts his eyes for longer than a second.

Panicker and Nair *et al.* [9] proposed worked based on computer vision methods provides a unique methodology for the detection of open eyes that may be employed sleepiness in the driver studies. A low-resolution camera is used to capture the driver footage in the suggested technique. There are three steps to the proposed drowsiness detection system. Face recognition is carried out. In the initial stage utilizing elliptical approximation and template matching algorithms. The open eye is recognized in the second step utilizing the suggested pattern study of the iris and sclera approach. The percentage of the eye closer (PERCLOS) metric is used to determine the driver's drowsy level in the third stage. For a variety of eye positions, it has been shown to operate well with low-resolution pictures. On photographs with variable illumination and complicated backgrounds, this approach produces good results.

3. MATERIALS AND METHOD

A purpose for this research focuses on create a system of estimating a driver's level of drowsiness using a series of images that are captured in a way that makes person’s face looks visual. The driver-based advanced driver assistance system (ADAS) [10] that the drowsiness detecting structure advanced within such study is a part of two key constraints: early detection and a reduction in the amount of false positives. Determining the frame rate which a camera must provide to the system in order to record the driver is crucial. Due to the large number concerning frames per second (FPS) can be examined, a high frame rate will overburden the machine [11], [12]. However, a low FPS might have a significant impact on the system's performance. To understand aspects to sequence image which extremely brief duration, such blinks, in this field, there must be a sufficient number of FPS.

3.1. Dataset descriptions

A facial data had been used from (Kaggle) website, which in turn serves the public interest and students of knowledge and provides them with ready-to-use data [13]. The training showed that the efficiency in the prediction was not satisfactory, after that the addition of 1000 images and merged it with the data that had previously utilized and then re-entered it into the algorithm and repeated the training phase, which usually takes time to extract the results where the first training took more than two days and the second training for more than 3 days. Also, no satisfactory results were shown, as enhanced the data with a large group of images, where the number of images reached 6000 images consisting of several different ages (the elderly, middle-aged, and scattered) and this includes both genders, where the results that were used had been extracted [14]. Drowsiness detection has an algorithm which is based on the MATLAB programming language to identify and detect the driver drowsiness. In this paper describe the main tools used for this algorithm.

3.2. Dlib open source library

Functions for face and landmark detection are available in the Dlib library. While Dlib's landmark detection is based on Kazemi's model, histogram-oriented approaches histogram of oriented gradients (HOG) are used for face detection [15], [16]. It provides 68 distinct feature points from a face. The placements of the 68 points that were found on a face are shown in Figure 1.

Figure 1. The 68 points positions identified on a face

3.3. Eye aspect ratio

A scalar variable called EAR reacts, notably when the eyes open and close [17]. Pandey and Muppalaneni [18] created a drowsiness identification and accident prevention system based on blink length and their system has demonstrated high accuracy on a dataset of yawning (YawDD). They employed an EAR threshold of 0.4 to differentiate between the open and closed states of the eye. The trend of time required to determine a typical EAR value for one blink is shown in Figure 2 [19]. We can see that the EAR value changes quickly during the flashing operation, either increasing or decreasing [20]. In accordance with the findings of earlier research, we employed threshold values to pinpoint the abrupt rise or fall in EAR values brought on by blinking.

According to earlier study, we are aware that using a threshold of 0.3 is advantageous for the current project. Numerous more methods for blink detection employing image processing techniques have also been proposed in the literature, in addition to this one. They do have certain limitations, though, such stringent requirements for picture and text quality, which are hard to get around. In our experiment, we chose EAR thresholds of 0.2 and 0.3 based on the findings of prior studies [21]. The advantage of being able to recognize faces from a distance is that the EAR formula is indifferent to the direction and proximity of the face. By entering the six coordinates around the eyes in Figures 3(a) and (b) into (1) and (2), the EAR value is calculated.

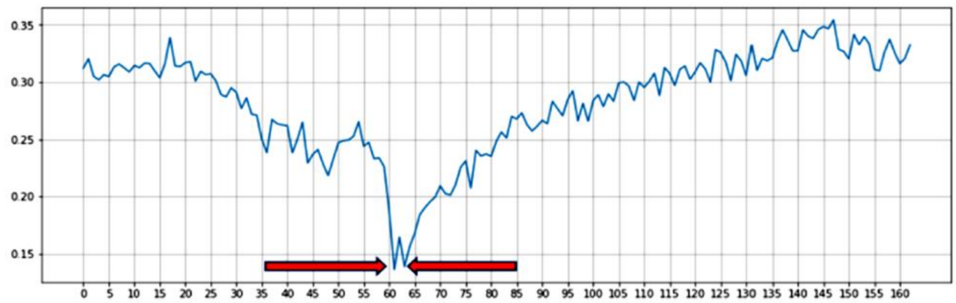
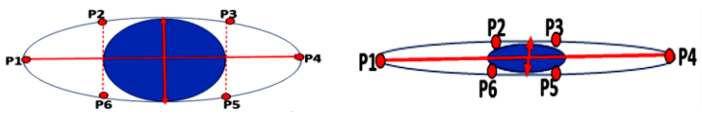


Figure 2. The initial blink is recognized using a single blink detection technique between frames 60 and 65



(a) (b)

Figure 3. Eyes examples that are (a) open eyes and (b) closed eyes, and have facial landmarks (P1-P6)

3.4. Facial landmark recognition algorithm

Facial landmark recognition algorithms are computer vision techniques designed to identify and locate specific facial landmarks or keypoints on a human face. These algorithms play a crucial role in various applications such as face analysis, facial expression recognition, face tracking, augmented reality, and drowsiness detection systems [22]. Finding the face in the image as well as identifying the points which create the face structure are the goals of facial landmark. The facial landmark recognition algorithm will identify 68 major points in accordance with the coordinates (x, y) that make up the human face in order to complete these two tasks [23], hence identifying the mouth, left eyebrow, right eyebrow, left eye, right eye, nose, and jaw.

3.5. Feature extraction and image classification using deep learning multi-task cascaded convolutional neural networks

The following procedure provides a clearer description of the three steps of multi-task cascaded convolutional neural networks (MTCNN) [24]:

a. The MTCNN initially produces numerous frames that scan the complete picture from top left corner to bottom right corner, starting from top left corner and finally moving towards bottom right corner. The proposal network (P-v Net), a shallow and fully linked CNN is used for information retrieval.
b. The second stage involves feeding the refinement network (R Net), a fully linked and complicated CNN that rejects the majority of frames that don't include faces with all the data from the P-Net.
c. The third step uses a more advanced CNN called output network (O-Net), which, as its name implies, outputs the facial landmark location after identifying a face in the provided picture or video [25], as seen in Figure 4.

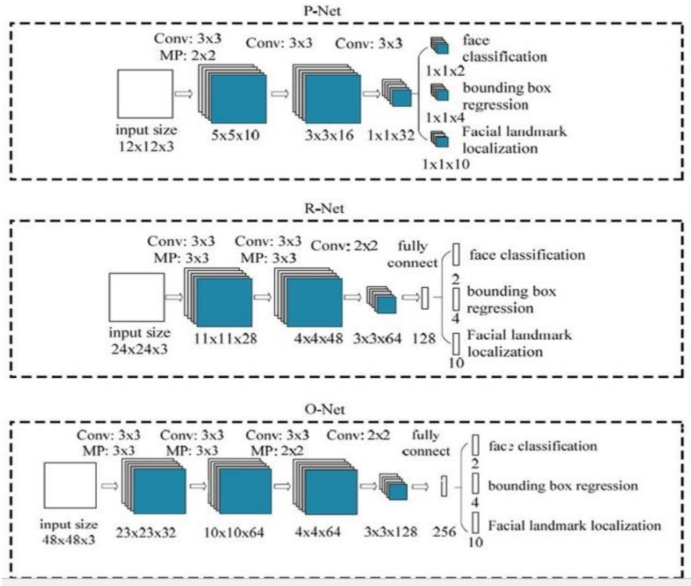


Figure 4. The three stages of MTCNN [16]

This method increases processing power features by distributed every 10 features among single stages and sub windows. OpenCV and MATLAB were used to develop the cascade classifier. For identifying faces in photos, the Haar cascade classifier makes use of Haar characteristics. The cascade approach will be used to evaluate each sub window in accordance with its feature [26]. In Figure 4, the classifier starts the assessment and examines each sub-property. Window's the sub window will proceed through the phases if it receives a favorable classification (face). The negative sub window (not the face) will reject right away in the alternative scenario. By deleting nonface-related windows at the start, this technique will boost the detection power of the face.

4. EXPERIMENTS RESULTS

The experimental results show how well the suggested behavioral data distribution service (DDS), which is based on a digital camera and the MTCNN deep learning algorithm, performs. The system can consistently detect sleepy states thanks to its great accuracy and precision, which reduces the likelihood of false alarms. The system may probably correctly identify most cases of sleepiness, according to the good recall rate, which lowers the possibility of false negatives. The global face features, such as the positions of the left and right eyes, nose, and corners of the mouth, can be determined by using the depth cascading multitasking MTCNN framework, which allows for simultaneous face detection and alignment. The internal relationship between the two is also exploited to improve performance, and to find drowsy you use to tow condition.

4.1. Normal detection case open eyes split lips

In this case, the eye is open and the mouth is closed. This stage is called awake or normal. Samples were taken as shown in the Table 1. It is worth noting that these samples in the mentioned case were taken in good lighting. The first scenario represents the test sample results and it turns out that the threshold value is 47. Figure 5 also shows the ratio of the mouth to the eye MOE, which shows that when the mouth is closed and the eye is open, the ratio's value is greater than the threshold value in the table.

Table 1. Normal detection case open eye close mouth

Samples	Number of monitoring	Number of detections	Threshold	MOE
10	10	9	47	46
10	10	10	47	49
10	10	10	47	50
10	10	10	47	52
10	10	10	47	53
10	10	10	47	54
10	10	10	47	55
10	10	10	47	56
10	10	10	47	56
10	10	10	47	57
Accuracy	100%	99.9%		

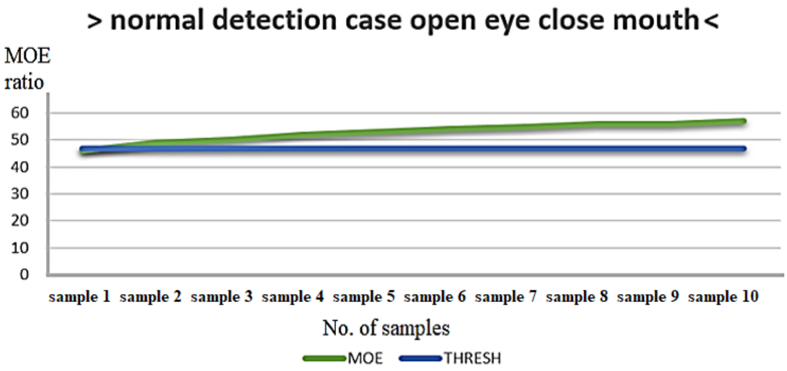


Figure 5. The ratio of MOE for the first case

4.2. Drowsiness detection case close eye close mouth

In this case, the eye is closed and the mouth is closed. This stage is called drowsiness. Samples were taken as shown in the Table 2. It is worth noting that these samples in the aforementioned case were taken in good lighting.

Table 2. Drowsiness detection case close eye close mouth

Samples	No. of monitoring	No. of detection	Threshold	MOE
10	10	10	47	39
10	10	10	47	40
10	10	10	47	41
10	10	10	47	44
10	10	10	47	44
10	10	10	47	45
10	10	10	47	45
10	10	9	47	49
10	10	10	47	43
10	10	10	47	44
Accuracy	100%	99.9%		

In the second case, the results from the tested samples are shown, and it turns out that the value of threshold=47, and the ratio of mouth to eye appears in the above values, where it turns out that when the eye is closed and the mouth is closed, its value is less than the value of threshold as shown in Figure 6. When a comparison is made to the performances of DDS with previous works in terms of accuracy, it can be seen that a very high accuracy is noticed as shown in Table 3 with other two references.

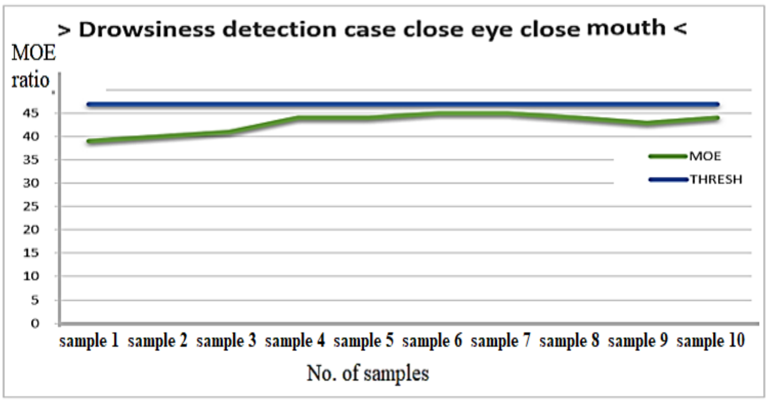


Figure 6. The ratio of MOE for the second case

Table 3. A comparative works

Ref.	Strategic	Percentage (%)
[8]	Use smart glasses-based drowsiness-fatigue-detection and cloud platform	98.4
[9]	Use novel algorithm for detecting faces (KCF and deep learning networks)	93
	Proposed method uses digital camera based on deep learning	99.9

4.3. Normal detection open eye close mouth

Additionally, we described how this impact would be seen on the detection of the eyes and lips when awake, but this time in dim illumination. According to Table 4, the findings from the tested samples reveal that the threshold value is 44, and the ratio of the mouth to the eye is shown in Figure 7. It comes out that when the mouth is closed and the eye is open, the ratio's value is lower and equal to the threshold value as shown in the table.

Table 4. Bad light case open eye close mouth

Samples	No. of monitoring	No. of detection	Threshold	MOE
10	10	9	44	40
10	10	10	44	48
10	10	10	44	46
10	10	10	44	44
10	10	10	44	45
10	10	10	44	47
10	10	10	44	41
10	10	9	44	52
10	10	10	44	53
10	10	10	44	51
Accuracy	100%	99.8%		

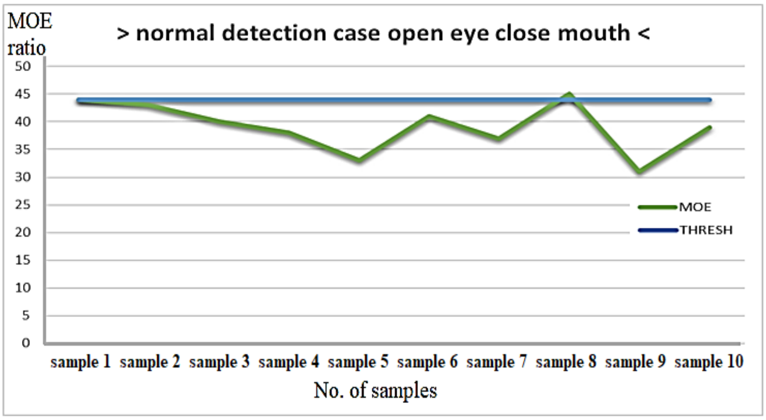


Figure 7. The ratio of MOE for the second case

4.4. Case 4 drowsiness detection case close eye close mouth

Both the mouth and the eye are closed in this instance. Drowsiness is the term for this phase. As indicated in Table 5, samples were collected. The fact that these samples in the aforementioned situation were obtained in poor lighting should be noted. The results from the tested samples are displayed in this case and it turns out that the value of threshold=44. The ratio of the mouth to the eye is also shown in the values, and it turns out that when both the mouth and the eye are closed, the ratio's value is lower than the value of the threshold as shown in Figure 8.

Now, a discussion of the collected results from both cases and a comparison to earlier efforts. The first scenario demonstrates the result that is dependent on the driver being blind and calculates the impact of each EAR and mouth aspect ratio (MAR) threshold. It was observed that the suggested model had improvements. This model has drowsiness detection capabilities and can notify the driver with a notice. When compared to other research, the model used in the suggested approach is also one from a majority effective way for detecting drowsiness. According to the preceding section, the outcome of the detection of drowsiness in this situation (without glasses) may reach 99% for both the EAR and MAR.

Table 5. Drowsiness detection case close eye close mouth in bad light

Samples	Number of monitoring	No. of detection	Threshold	MOE
10	10	10	44	31
10	10	10	44	32
10	10	10	44	33
10	10	9	44	45
10	10	10	44	36
10	10	10	44	36
10	10	10	44	36
10	10	9	44	47
10	10	10	44	37
10	10	10	44	37
Accuracy	100%	99.8%		

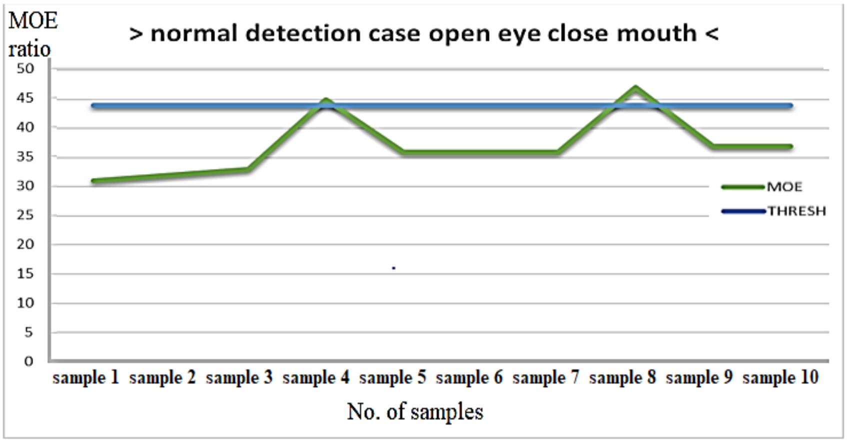


Figure 8. Case of drowsiness detection, close eye close mouth

5. CONCLUSION

One of a major contribution in this research has a generation for the new benchmark for a system for driver drowsing detection because of the drowsiness risk. It is substantial for the driver to use safer schemes, like staying away from driving at night, avoiding medication and alcohol, acquiring a good amount of sleep, and drinking more caffeine. One of the most significant strategies for reducing traffic accidents is to do research on sleepy driving detection algorithms. We present a novel driving drowsiness detection method that takes different variations into account in this study. To acquire a face of the driver in real-time video, first created a MTCNN model, that eliminates the method to fake feature removal in standard a face identification technique. Face recognition accuracy can approach 99.99%, according to experimental data. EAR and MAR as measurement. Whereas EAR, a different parameter depended on the Dlib toolkit, was proposed to analyze the condition to the driver's eyes, experiments demonstrate that there is the significant link among EAR as well as a value for the driver eye. While MAR, it's also a different parameter depended at a Dlib toolkit for a purpose for analyzing a condition to the driver mouth. Because of the experiment demonstrating that there is substantial link between the MAR and the effect the mouth of the drivers on the eye. Because of the muscle twitch of the muscles in the event of opening and closing the mouth on the face, demonstrating the logic of this theory.

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